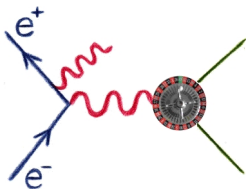


A combined estimate of the KLOE08, KLOE10 and KLOE12 ISR measurements

S. E. Müller

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*Radio MonteCarLOW Meeting
LNF Frascati, 13-14 September 2013*

The KLOE data sets

- **KLOE05**: 60 points between 0.35 and 0.95 GeV², based on 141.4 pb⁻¹ of data taken in 2001^a
- **KLOE08**: 60 points between 0.35 and 0.95 GeV², based on 240.0 pb⁻¹ data taken in 2002^b
- **KLOE10**: 75 points between 0.1 and 0.85 GeV², based on 232.6 pb⁻¹ data taken in 2006^c with $\sqrt{s} = 1.00$ GeV
- **KLOE12**: 60 points between 0.35 and 0.95 GeV², based on 240.0 pb⁻¹ data taken in 2002^d, normalized to muons

^aPhys. Lett. B**606** (2005) 12

^bPhys. Lett. B**670** (2009) 285

^cPhys. Lett. B**700** (2011) 102

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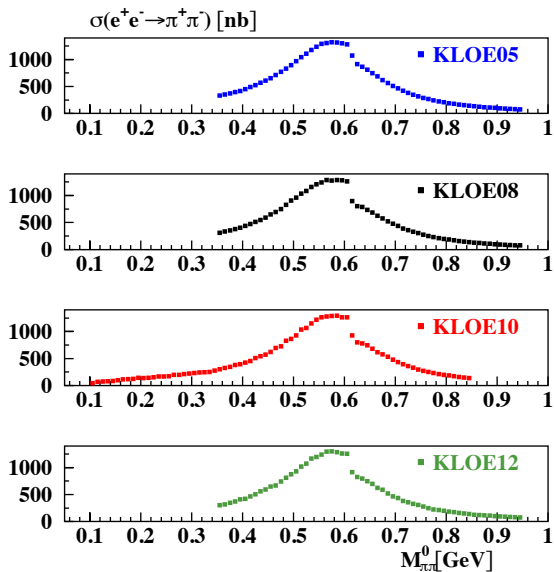
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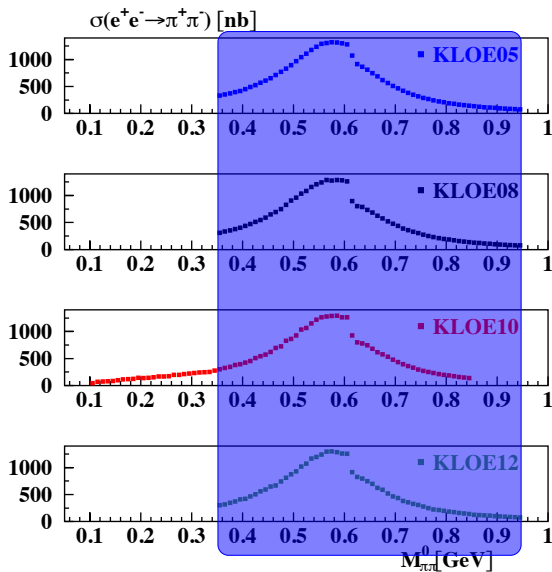
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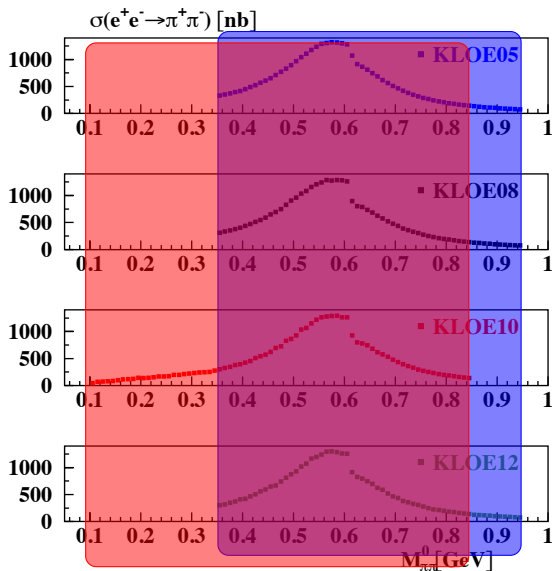
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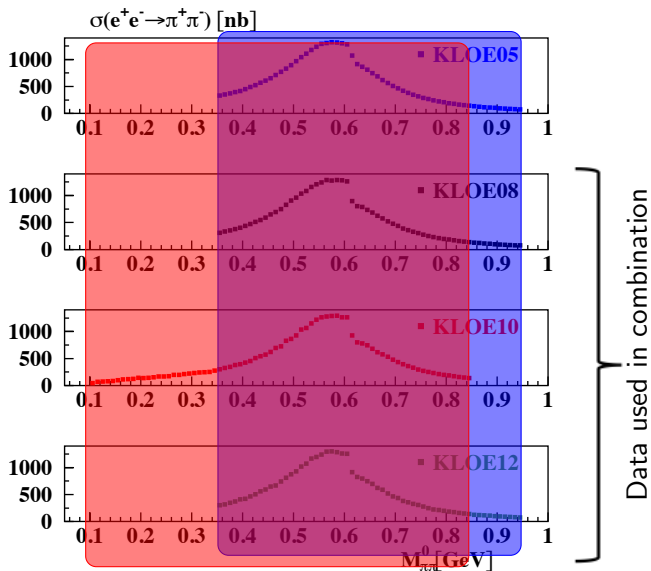
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BLUE: Best linear unbiased estimate¹

We have 195 $y_i = \{y_1, \dots, y_{195}\}$ measurements for the 85 observables with true value $X_\alpha = \{X_1, \dots, X_{85}\}$ (the 85 bins between 0.1 and 0.95 GeV²).

Find the **B**est **L**inear **U**nbiased **E**stimates \hat{x}_α of the 85 observables such that

- A the \hat{x}_α are a **linear** combination of the input measurements y_i
- B the \hat{x}_α are **unbiased** estimates of the true values X_α
- C the \hat{x}_α minimize the variance $var(\hat{x}_\alpha) \equiv cov(\hat{x}_\alpha, \hat{x}_\alpha)$ (they are the **best** estimates)

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- condition A gives

$$\hat{x}_\alpha = \sum_{i=1}^{195} \lambda_{\alpha i} y_i \equiv \sum_{\beta=1}^{85} \sum_{i=1}^{195} \lambda_{\alpha i} \mathcal{U}_{i\beta} y_i \quad (1)$$

- condition B gives the normalization constraints

$$\sum_{i=1}^{195} \lambda_{\alpha i} \mathcal{U}_{i\beta} = \delta_{\alpha\beta} \quad (2)$$

- condition C requires to determine the linear weights $\lambda_{\alpha i}$ such that they minimize the variances of the \hat{x}_α :

$$\text{var}(\hat{x}_\alpha) \equiv \text{cov}(\hat{x}_\alpha, \hat{x}_\alpha) = \sum_{i=1}^{195} \sum_{j=1}^{195} \lambda_{\alpha i} \mathcal{M}_{ij} \lambda_{\alpha j}, \quad (3)$$

where \mathcal{M}_{ij} is the (195,195) covariance matrix of the 195 measurements.

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BLUE: Best linear unbiased estimate

Task: Determine the $\lambda_{\alpha i}$ defined by condition *A* by minimizing the variances in condition *C* under the constraints given by condition *B*! Introducing the Lagrange multipliers $K_{\alpha\beta}$, the object to minimize becomes

$$\left[\text{var}(\hat{x}_\alpha) + 2 \sum_{\gamma=1}^{85} K_{\alpha\gamma} (\delta_{\alpha\gamma} - \sum_{j=1}^{195} \lambda_{\alpha j} \mathcal{U}_{j\gamma}) \right] \quad (4)$$

Differentiating with respect to $K_{\alpha\gamma}$ and $\lambda_{\alpha j}$ gives

$$\left\{ \begin{array}{l} \delta_{\alpha\beta} - \sum_{j=1}^{195} \lambda_{\alpha j} \mathcal{U}_{j\beta} = 0 \quad \forall \alpha, \forall \beta, \\ \left(\sum_{j=1}^{195} \mathcal{M}_{ij} \lambda_{\alpha j} \right) - \left(\sum_{\gamma=1}^{85} K_{\alpha\gamma} \mathcal{U}_{i\gamma} \right) = 0 \quad \forall \alpha, \forall i \end{array} \right.$$

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BLUE: Best linear unbiased estimate

The system of linear equations is solved by

$$K_{\alpha\gamma} = (\mathcal{U}^T \mathcal{M}^{-1} \mathcal{U})_{\alpha\gamma}^{-1} \quad (5)$$

$$\lambda_{\alpha i} = \sum_{\beta=1}^{85} (\mathcal{U}^T \mathcal{M}^{-1} \mathcal{U})_{\alpha\gamma}^{-1} (\mathcal{U}^T \mathcal{M}^{-1})_{\beta i} \quad (6)$$

$$\text{cov}(\hat{x}_\alpha, \hat{x}_\beta) = (\mathcal{U}^T \mathcal{M}^{-1} \mathcal{U})_{\alpha\beta}^{-1} \quad (7)$$

Knowing the two matrices $\mathcal{U}_{i\alpha}$ and \mathcal{M}_{ij} allows to determine the linear coefficients $\lambda_{\alpha i}$ and therefore the Best Unbiased Linear Estimates \hat{x}_α .

The $\mathcal{U}_{i\alpha}$ matrix

is a $(\underbrace{195}_{\text{rows}} \times \underbrace{85}_{\text{cols}})$ matrix linking the measurements y_i to the observables

X_α

$$\mathcal{U}_{i\alpha} = \begin{cases} 1 & \text{if } y_i \text{ is a measurement of } X_\alpha, \\ 0 & \text{if } y_i \text{ is not a measurement of } X_\alpha, \end{cases}$$

The $\mathcal{U}_{i\alpha}$ matrix

$$\mathcal{U} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 1 \\ \\ 1 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & \dots & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & \dots & 0 & 0 \\ \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 1 \end{pmatrix}$$

→ bins in $M_{\pi\pi}^2$ (0.1 - 0.95 GeV²)

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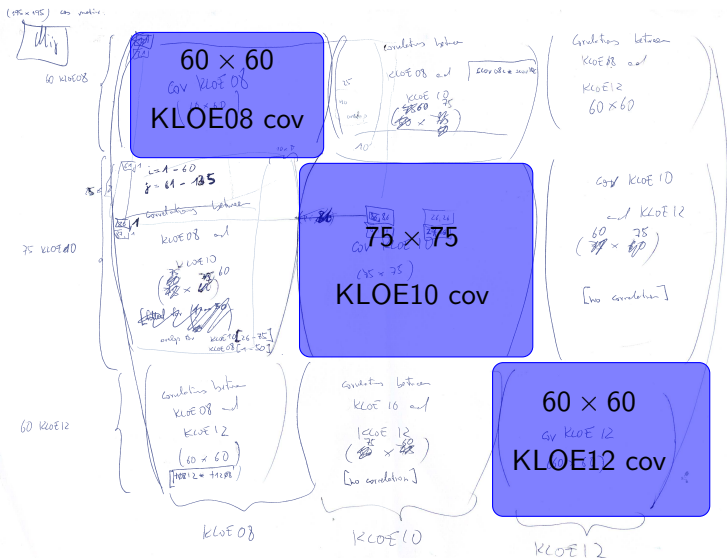
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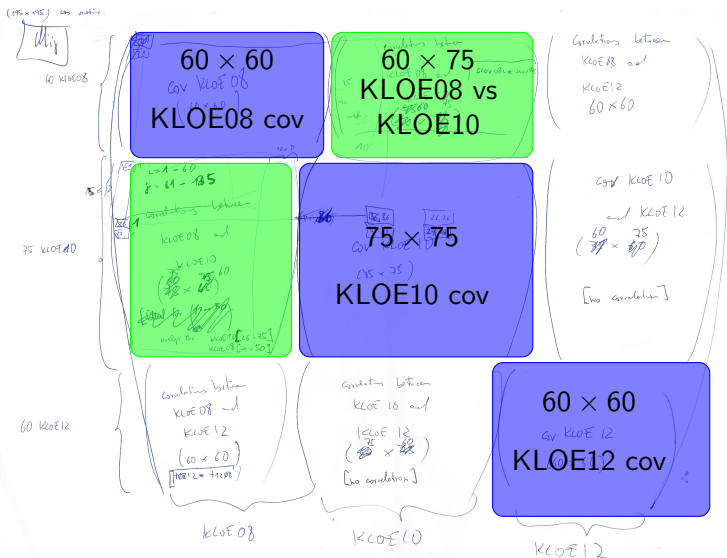
The M_{ij} matrix

is the covariance matrix for the $60 + 75 + 60 = 195$ data points.



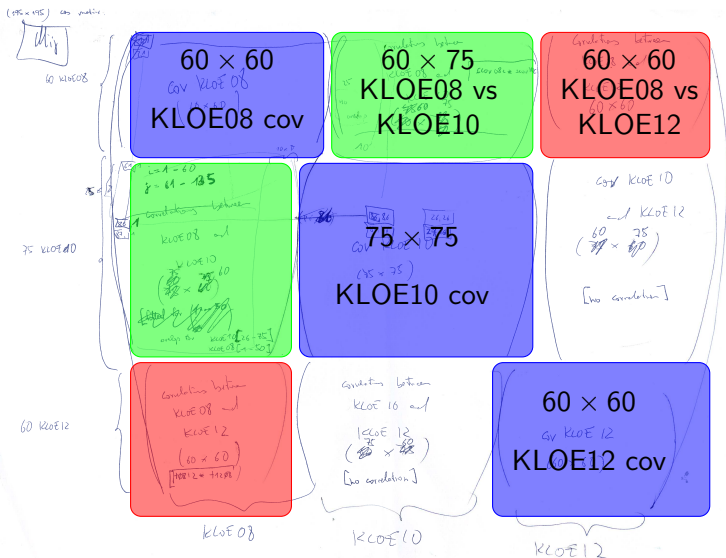
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A caveat: normalization errors

G. D'Agostini (NIM A346 (1994) 306):

Normalization errors (e.g. errors on scale factors) can create a bias when fitting correlated data

The problem of finding the linear unbiased estimates of minimum variance for the 85 observables X_α is equivalent to the problem of finding the estimates \hat{x}_α minimizing the quantity

$$S = \sum_{i=1}^{195} \sum_{j=1}^{195} [y_i - (\mathcal{U} \hat{x})_i] \mathcal{M}_{ij}^{-1} [y_j - (\mathcal{U} \hat{x})_j] \quad (8)$$

However, only the free parameters \hat{x}_α are varied (within the errors) to find the minimum of S . But in the case of a normalization error, also the elements of \mathcal{M}_{ij} should be scaled accordingly when varying the \hat{x}_α . Therefore, normalization errors lead to a bias in this method.

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Way out: Two separate covariance matrices:

- $\mathcal{M}_{ij}^{\text{stat}}$ which contains the statistical uncertainties and is used to find the \hat{x}_α
- $\mathcal{M}_{ij}^{\text{syst}}$ which contains all the normalization errors, gives

$$\text{cov}^{\text{syst}}(\hat{x}_\alpha, \hat{x}_\beta) = \sum_{i=1}^{195} \sum_{j=1}^{195} \lambda_{\alpha i} \mathcal{M}_{ij}^{\text{syst}} \lambda_{\beta j}, \text{ which can then be added to}$$

$$\text{cov}^{\text{stat}}(\hat{x}_\alpha, \hat{x}_\beta):$$

$$\text{cov}^{\text{tot}}(\hat{x}_\alpha, \hat{x}_\beta) = \text{cov}^{\text{stat}}(\hat{x}_\alpha, \hat{x}_\beta) + \text{cov}^{\text{syst}}(\hat{x}_\alpha, \hat{x}_\beta) \quad (8)$$

The \mathcal{M}_{ij} matrix: The 3 diagonal blocks

- $\mathcal{M}_{ij}^{\text{stat}}$: Take the data files provided at the KLOE ppg webpage for each analysis <http://www.lnf.infn.it/kloe/ppg/>
- $\mathcal{M}_{ij}^{\text{syst}}$: For each contribution to the systematic error (given at the webpage), construct the corresponding contribution to the matrix element via $\delta_{ij}^{\text{xxxx}} = +1 \cdot \delta_i^{\text{xxxx}} \delta_j^{\text{xxxx}}$, and add the contributions:

$$\mathcal{M}_{ij}^{\text{syst}} = \delta_i^{\text{trig}} \delta_j^{\text{trig}} + \delta_i^{\text{Bkg}} \delta_j^{\text{Bkg}} + \delta_i^{\text{Lumi}} \delta_j^{\text{Lumi}} + \dots \quad (9)$$

Exception: Errors on unfolding for KLOE08 and KLOE10 - one can assume them to be fully anti-correlated, and therefore it contributes with $\delta_{ij, i \neq j}^{\text{Unf}} = -1 \cdot \delta_i^{\text{Unf}} \delta_j^{\text{Unf}}$ to the off-diagonal elements.

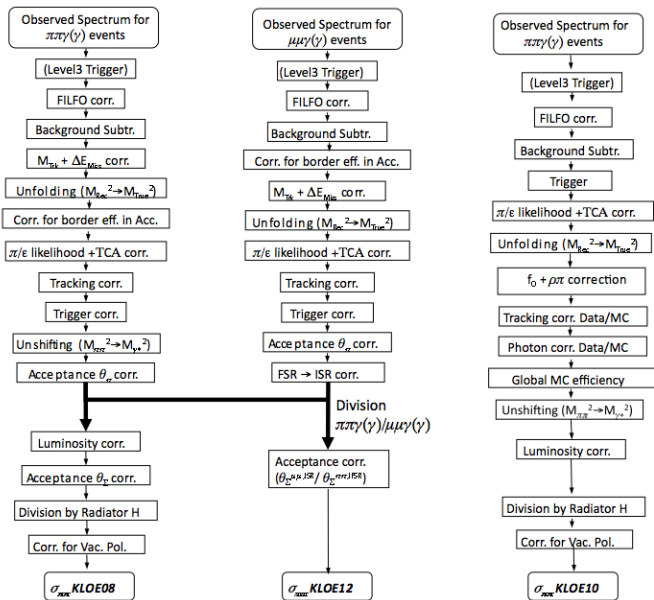
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- $\mathcal{M}_{ij}^{\text{syst}}$: For each contribution to the systematic error (given at the webpage), construct the corresponding contribution to the matrix element via $\delta_{ij}^{\text{xxxx}} = +1 \cdot \delta_i^{\text{xxxx}} \delta_j^{\text{xxxx}}$, and add the contributions:

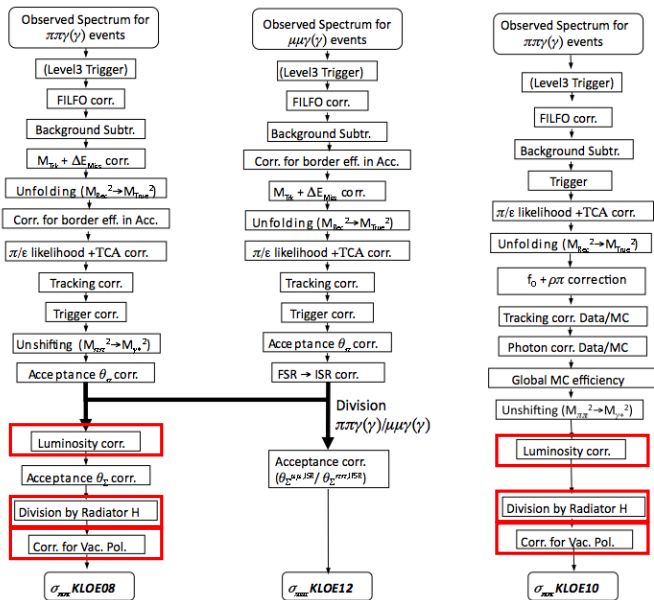
$$\mathcal{M}_{ij}^{\text{syst}} = \delta_i^{\text{trig}} \delta_j^{\text{trig}} + \delta_i^{\text{Bkg}} \delta_j^{\text{Bkg}} + \delta_i^{\text{Lumi}} \delta_j^{\text{Lumi}} + \dots \quad (9)$$

Exception: Errors on unfolding for KLOE08 and KLOE10 - one can assume them to be fully anti-correlated, and therefore it contributes with $\delta_{ij, i \neq j}^{\text{Unf}} = -1 \cdot \delta_i^{\text{Unf}} \delta_j^{\text{Unf}}$ to the off-diagonal elements.

The M_{ij} matrix: The KLOE08 - KLOE10 correlation block



The M_{ij} matrix: The KLOE08 - KLOE10 correlation block



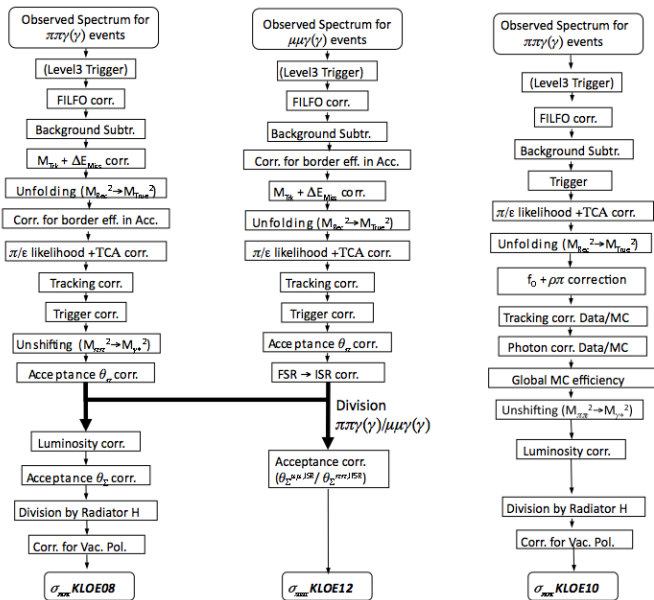
The \mathcal{M}_{ij} matrix: The KLOE08 - KLOE10 correlation block

- $\mathcal{M}_{ij}^{\text{stat}}$: In this case, there are no contribution to the statistical covariance matrix.
- $\mathcal{M}_{ij}^{\text{syst}}$: The following contributions to the systematic uncertainty are common to both analyses:
 - ▶ uncertainty on luminosity evaluation (0.3%)
 - ▶ uncertainty on radiator function (0.5%)
 - ▶ uncertainty on vacuum polarization correction (from F. Jegerlehner's routine)

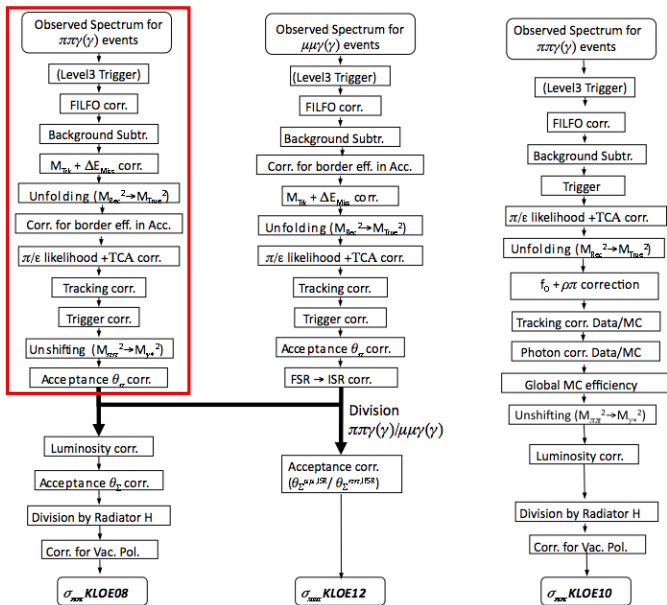
Therefore, the elements of $\mathcal{M}_{ij}^{\text{syst}}$ are constructed like this:

$$\mathcal{M}_{ij}^{\text{syst}} = \delta 08_i^{\text{Lumi}} \delta 10_j^{\text{Lumi}} + \delta 08_i^{\text{Radiator}} \delta 10_j^{\text{Radiator}} + \delta 08_i^{\text{VacPol}} \delta 10_j^{\text{VacPol}} \quad (10)$$

The M_{ij} matrix: The KLOE08 - KLOE12 correlation block



The M_{ij} matrix: The KLOE08 - KLOE12 correlation block



The \mathcal{M}_{ij} matrix: The KLOE08 - KLOE12 correlation block

- $\mathcal{M}_{ij}^{\text{stat}}$: “Intermediate” covariance matrix $\mathcal{M}_{ij}^{\text{int}}$ up to the acceptance correction for θ_π for the KLOE08 analysis, then propagate this matrix towards $\sigma_{\pi\pi}^{08}$ and $\sigma_{\pi\pi}^{12}$ by applying the remaining correction factors:

$$\mathcal{M}_{ij}^{08} = \frac{\mathcal{M}_{ij}^{\text{int}}}{(0.01\text{GeV}^2)(\text{Acc}_{\theta_\Sigma})(\int \mathcal{L} dt)(H(s_\pi, s))\delta_{VP}} \quad (11)$$

$$\mathcal{M}_{ij}^{12} = \frac{\mathcal{M}_{ij}^{\text{int}}}{N_{\mu\mu\gamma}^{\text{vis}}} \left(\text{Acc}_{\Sigma} \frac{\theta_{\mu\mu\gamma, \text{ISR}}}{\theta_{\pi\pi\gamma, \text{ISR}}} \right) \times \text{kin. factors} \quad (12)$$

$$\mathcal{M}_{ij}^{\text{stat}} = \sqrt{\mathcal{M}_{ij}^{08} \mathcal{M}_{ij}^{12}} \quad (13)$$

The \mathcal{M}_{ij} matrix: The KLOE08 - KLOE12 correlation block

- $\mathcal{M}_{ij}^{\text{syst}}$: The following contributions to the systematic uncertainty are common to both analyses:
 - ▶ uncertainty from L3 trigger in KLOE08 analysis (0.1%)
 - ▶ uncertainty on background evaluation of the KLOE08 $\pi\pi\gamma$ analysis (tabulated in KLOE08 publication)
 - ▶ uncertainty on cuts on M_{trk} and ΔE_{miss} in KLOE08 analysis (0.2%)
 - ▶ uncertainty on unfolding in KLOE08 analysis (only in 5 bins between 0.58 – 0.63 GeV^2), considered fully anti-correlated
 - ▶ uncertainty on tracking efficiency in KLOE08 analysis (0.3%)
 - ▶ uncertainty on trigger efficiency in KLOE08 analysis (0.1%)
 - ▶ uncertainty on acceptance in KLOE08 analysis (tabulated in KLOE08 publication)

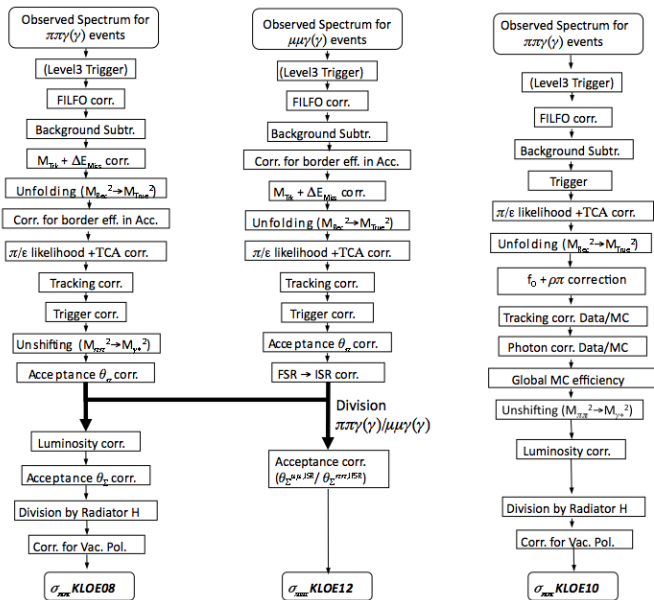
The \mathcal{M}_{ij} matrix: The KLOE08 - KLOE12 correlation block

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 - ▶ uncertainty on trigger efficiency in KLOE08 analysis (0.1%)
 - ▶ uncertainty on acceptance in KLOE08 analysis (tabulated in KLOE08 publication)

Therefore, the elements of $\mathcal{M}_{ij}^{\text{syst}}$ are constructed like this:

$$\begin{aligned}\mathcal{M}_{ij}^{\text{syst}} = & \delta 08_i^{\text{L3}} \delta 12_j^{\text{L3}} + \delta 08_i^{\text{bg}} \delta 12_j^{\text{bg}} + \delta 08_i^{\text{TM}, \Delta E} \delta 12_j^{\text{TM}, \Delta E} + \\ & + \delta 08_i^{\text{trk}} \delta 12_j^{\text{trk}} + \delta 08_i^{\text{trg}} \delta 12_j^{\text{trg}} + \delta 08_i^{\text{acc}} \delta 12_j^{\text{acc}} + \\ & + \rho_{\text{unf}} \delta 08_i^{\text{unf}} \delta 12_j^{\text{unf}}\end{aligned}$$

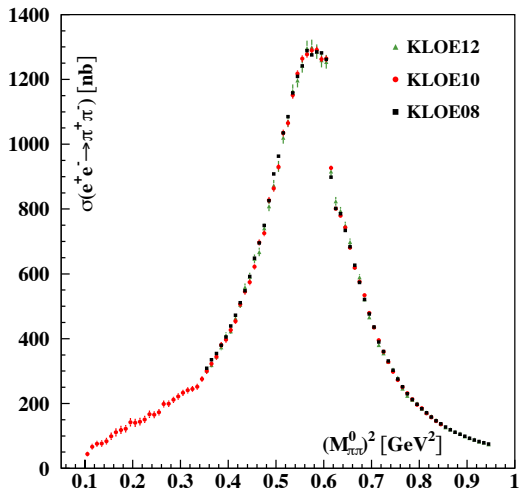
The M_{ij} matrix: The KLOE10 - KLOE12 correlation block



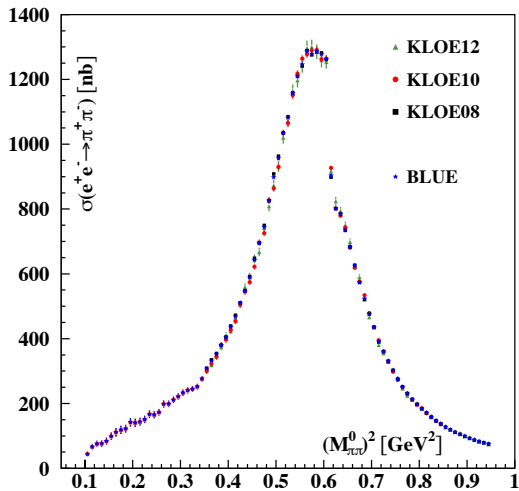
The \mathcal{M}_{ij} matrix: The KLOE10 - KLOE12 correlation block

- $\mathcal{M}_{ij}^{\text{stat}}$: In this case, there are no contributions to the statistical covariance matrix.
- $\mathcal{M}_{ij}^{\text{syst}}$: There are no contributions to the systematic uncertainty that are common to both analyses!

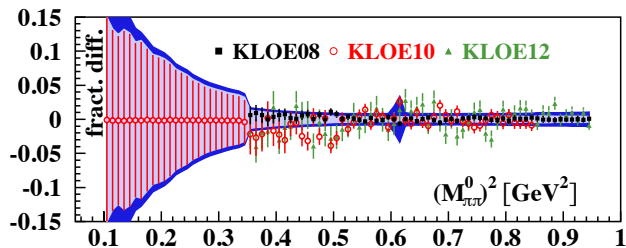
The result



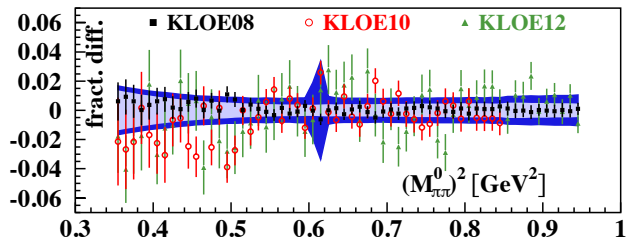
The result



The result

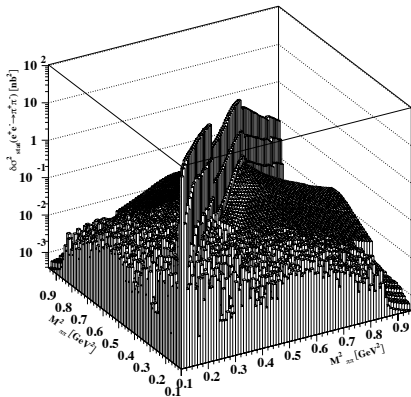


The result

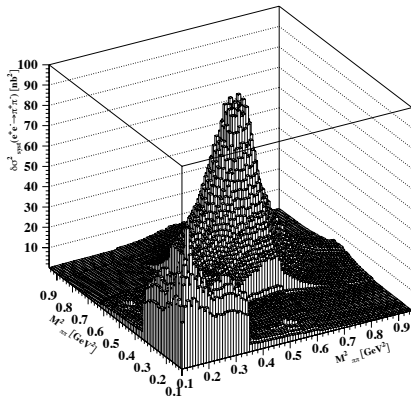


The covariance matrices for the BLUE values

stat. covariance matrix:



syst. covariance matrix:



To obtain the total covariance matrix, simply add the two.

Dispersion integral for a_μ^{had}

Evaluating a_μ^{had} between $s_{\text{min}} = 0.1 \text{ GeV}^2$ and $s_{\text{max}} = 0.95 \text{ GeV}^2$ with a binned data set of $n = 85$ points with binwidth $\Delta s = 0.01 \text{ GeV}^2$:

$$a_\mu^{\text{had}}[s_{\text{min}}, s_{\text{max}}] = \frac{1}{4\pi^3} \int_{s_{\text{min}}}^{s_{\text{max}}} \sigma^{\text{had}}(s) K(s) ds \simeq \frac{1}{4\pi^3} \sum_{i=1}^n \sigma_i^{\text{had}} K_i \Delta s$$

With $c_i \equiv \partial a_\mu^{\text{had}} / \partial \sigma_i = (1/4\pi^3) K_i \Delta s$ we obtain for the uncertainty on a_μ^{had}

$$\begin{aligned} \left(\sigma_{a_\mu^{\text{had}}} \right)^2 &= \sum_{\alpha=1}^n \sum_{\beta=1}^n c_\alpha c_\beta [\text{cov}^{\text{tot}}(\hat{x}_\alpha, \hat{x}_\beta)]_{\alpha\beta} \\ &= \underbrace{\sum_{\alpha=1}^n c_\alpha^2 \text{var}(\hat{x}_\alpha)}_{\substack{\alpha=\beta, \\ \text{diagonal term}}} + \underbrace{\sum_{\alpha=1}^n \sum_{\substack{\beta=1 \\ \alpha \neq \beta}}^n c_\alpha c_\beta [\text{cov}^{\text{tot}}(\hat{x}_\alpha, \hat{x}_\beta)]_{\alpha\beta}}_{\substack{\alpha \neq \beta, \\ \text{off-diagonal term}}} \end{aligned}$$

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$$\begin{aligned} \left(\sigma_{a_\mu^{\text{had}}} \right)^2 &= \sum_{\alpha=1}^n \sum_{\beta=1}^n c_\alpha c_\beta [\text{cov}^{\text{tot}}(\hat{x}_\alpha, \hat{x}_\beta)]_{\alpha\beta} \\ &= \underbrace{\sum_{\alpha=1}^n c_\alpha^2 \text{var}(\hat{x}_\alpha)}_{\substack{\alpha=\beta, \\ \text{diagonal term}}} + \underbrace{\sum_{\alpha=1}^n \sum_{\substack{\beta=1 \\ \alpha \neq \beta}}^n c_\alpha c_\beta [\text{cov}^{\text{tot}}(\hat{x}_\alpha, \hat{x}_\beta)]_{\alpha\beta}}_{\substack{\alpha \neq \beta, \\ \text{off-diagonal term}}} \end{aligned}$$

Results on $a_{\mu}^{\pi\pi}$:

Using a combination of KLOE08 & KLOE10 (KLOE Note 225):

$$\Delta a_{\mu}^{\pi\pi}[0.10 - 0.95\text{GeV}^2] = (488.6 \pm 6.0) \times 10^{-10} \quad (11)$$

$$\Delta a_{\mu}^{\pi\pi}[0.35 - 0.85\text{GeV}^2] = (379.1 \pm 2.9) \times 10^{-10} \quad (12)$$

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Using the BLUE for KLOE08, KLOE10 & KLOE12:

$$\Delta a_{\mu}^{\pi\pi} [0.10 - 0.95\text{GeV}^2] = (488.6 \pm 5.7) \times 10^{-10} \quad (13)$$

$$\Delta a_{\mu}^{\pi\pi} [0.35 - 0.85\text{GeV}^2] = (378.9 \pm 2.8) \times 10^{-10} \quad (14)$$

Results on $a_{\mu}^{\pi\pi}$:

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Using the BLUE for KLOE08, KLOE10 & KLOE12:

$$\Delta a_{\mu}^{\pi\pi} [0.10 - 0.95\text{GeV}^2] = (488.6 \pm 5.7) \times 10^{-10} \quad (13)$$

$$\Delta a_{\mu}^{\pi\pi} [0.35 - 0.85\text{GeV}^2] = (378.9 \pm 2.8) \times 10^{-10} \quad (14)$$

Using the BLUE for KLOE08, KLOE10 & KLOE12, but correcting KLOE08 and KLOE10 for Fred Jegerlehner's 2012 corrections for vacuum polarization:

$$\Delta a_{\mu}^{\pi\pi} [0.10 - 0.95\text{GeV}^2] = (487.8 \pm 5.7) \times 10^{-10} \quad (15)$$

$$\Delta a_{\mu}^{\pi\pi} [0.35 - 0.85\text{GeV}^2] = (378.1 \pm 2.8) \times 10^{-10} \quad (16)$$

Summary and conclusion

- BLUE of KLOE08, KLOE10 and KLOE12 data have been evaluated
- Care needs to be applied in construction of covariance matrices (two separate matrices for statistical and systematic effects to avoid bias in construction of BLUE)
- Can't be done by people not familiar with the different analyses
- Still some cross checks needed, then result will be put on the KLOE ppg-webpage:
<http://www.lnf.infn.it/kloe/ppg/>